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AirCAST: a DSS for Business Decisions in Air Transportation

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Abstract. The socio-economic development leads people to a great mobility and the identification and management of flights is becoming a key factor to economic growth. The airport management is constantly looking for methods to improve its performance, both in terms of profitability and quality of service and the proper planning of passenger flows. In this work we introduce AirCAST, an efficient Decision Support System (DSS) framework based on the hybridization of a discrete event simulator and Logit models. This framework is the first application of simulation optimization techniques to the air flow forecasting problem and is able to cope different system settings. Moreover, differently from other works in literature, which focuses of large and hub airports, AirCAST is applied to two Italian regional airports. In this case, in fact, the application becomes more difficult due to the high density of airports in Europe, and Italy in particular, and the consequent intersection between the catchment areas. In order to show the effectiveness of the framework, we present the results of these two real cases studies.

Keywords. Air flow forecast, DSS, multinomial logit, simulation-optimization.

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1 Introduction

In the field of air transportation, the decisions on the flights that should be opened in a given an airport implies the study of demand, supply and the economic and spatial relationships between the different actors involved (airlines, passengers, airport management, public stakeholders). Many transformations are taking place in the air transportation market, due to the presence of different airlines and airports characterized by different costs and service levels, and in strong competition between each other. Moreover, public stakeholders (regional councils and municipalities) ask airports management to show the economic impact of new flights in order to give a financial support.

In order to understand and control this important phenomenon, it is necessary to model the competition in the system and measure the impact of the transformations, as well as to develop new methods for dealing with decisions inherent the potential increase in profit and traffic due to changes in their offers (IATA, 2008, 2010). This issue is interesting not only from a practical point of view, due to its relevant economic impact, but also for its research impact. In fact, the complexity of the systems under study and the strong relationship between the different actors make the problem challenging also from the point of view of the research on transportation systems.

This paper contributes to advance the current state-of-the-art along two axes. First, the paper introduces a new modeling approach for air flow forecasts by means of hybridization of simulation and optimization. In this way, our method is able to model not only the passengers choice, but also the uncertainty due to data of demand/supply. Second, we apply for the first time a forecasting tool to the Italian area. This area presents peculiar characteristics, included the high density (and the high level of competition) of airports. Moreover, differently to other studies, in our work we consider systems with regional and hub airports. Finally, we show how the developed framework can be used both to study the passengers flows and their economic impact in a given area.

In more details, in this paper we introduce AirCAST, a Decision Support System (DSS) for the forecasting of passengers flows. The heart of AirCAST is an efficient Logit formulation for modeling the competition between different airports and forecasting the effects of the introduction of modifications of the flight schedule in the system. In order to deal with the stochastic sources not taken into account by the Logit model, it is integrated with a simulation framework. To show the effectiveness of AirCAST, two case studies presenting different use of the system are presented. Both case studies focus on Italian airports. The first one is a typical application for forecasting the passengers when a new flight is added to an existing airport schedule, while the second one shows how the DSS can be used to give a measure of the economic impact of a new flight connection.

The paper is organized as follows. Section 2 gives a better insight on the problem and the related literature. The overall scheme of the DSS as well as the Logit model and an two applications of the framework are presented in Section 3 and 4, respectively. Finally Section 5 presents the final remarks and future developments.

2 Problem definition and state-of-the-art

Let us consider a set of airports for which we know the flights connecting each other, as well as the flight schedule and the overall passenger flow of each flight connection. Our aim is to predict the flows due to a frequency changes of an existing flight or to the opening of a new one between a given pair of airports.

The passengers in the catchment area of each airport are unknown, but some forecasts on this information are given. Then, the passenger number becomes a stochastic variable with unknown probability distribution. For each flight we know in advance the mean cost paid by a single passenger for taking the flight, as well as the quality parameters of the airports, including the time needed to reach the airport from the nearby area and the time needed to perform internal operations such as passport checks and luggage delivery.

While several applications of multinomial Logit Models can be found in other research field, as location and transportation (Tadei et al., 2009, 2010; Baik et al., 2008), the literature on airport-choice modeling mostly focused on two geographical areas: the San Francisco Bay area and the United Kingdom one. For what concerns the SF bay area, Nested Logit models based analysis on the correlation between the choice of airport and airline (Pels et al., 2001) and on the sensitivity to the airport access mode on the user choice has been studied (Pels et al., 2003). More recent studies introduced Mixed Multinomial Logit models for analyzing the joint choice of airport, airline, access modes and random taste heterogeneity (Hess and Polak, 2004, 2005b,a). Multinomial Logit Models has been realized for airport choice in the UK in order to study the most important attraction factors to airports (Ashford and Bencheman, 1987; Brooke et al., 1994) and market share forecasts for a new airport (Thompson and Caves, 1993). More recently, a Cross-Nested Logit model has been introduced in order to model the choice of airport, airline and access-mode on the Greater London area (Hess and Polak, 2006) showing improvements over the previous Nested and Multinomial Logit models. These methods show two main drawbacks. First, they focusing on specific typologies of airports (large-sized and hub), not considering challenging settings as the competition of regional airports. Second, the only source of stochasticity is the passenger choice, while other sources of uncertainty due to data estimate are not explicitly taken into account.

3 The AirCAST framework

Most of the modeling and optimization methods in the literature focus on one of the actors involved in the airport system (users, airport managers, government agencies and airlines), usually simplifying the complex cause-effect relationships between decision makers, in particular the behavior of passengers, and the uncertainties on demand or offer forecasts. Indeed, in air transportation one of the most frequent source of errors are due to passengers flows and their profiling according to given sub-categories, as well as the uncertainty about the demand in terms of passengers for each airport flight. Moreover, literature focuses on large and hub airports, where the catchment areas are usually well known and have marginal intersection with the catchment of the neighbor airports. On the other hand the increasing competition between regional airports forces to overcome these limits in the literature.

The base of this work is an economic and spatial interaction Logit model aimed at modeling the dependency between the actors. This kind of model shows a high adaptability to changing decision-making levers involved and a wide efficiency demonstrated in several fields, including transport and retail (Koppelman and Wen, 2000). Moreover, the method is applied to areas with a larger number of regional airports, where the catchment areas strongly intersected between each other. Modeling such a system requires the introduction of an analytical tool in order to evaluate the entire system behaviour and dealing with the uncertainties of the system.

Scientific research has recently focused on developing models that combine simulation and optimization. The simulator carries out the generation of possible scenarios of the system under analysis in order to evaluate the decisions taken by the model and predict their impact on the overall system and other actors of the decisions, considering the time as a variable of the system. The optimization block finds the optimal solution for each scenario starting from the parameters identified by the simulation and solving a combinatorial optimization problem.

The hybridization of the two systems allows to verify and refine the taken decisions. In particular, Simulation and Optimization methods allow to incorporate into the model the dynamic component of the system due to structural changes and to evaluate the effect of decisions over the medium term. Moreover, they are effective in finding a solution that is feasible for all the considered scenarios, and minimizing the deviation of the overall solution from the optimal solution for each scenario. Although some applications combine simulation and optimization using linear model, there is still significant potential for improvement (Better et al., 2008; Olafsson and Kim, 2002). The main direction that we investigate in this work is the introduction of non-linear models in the simulation and optimization framework.

Our framework combines an optimization model able to make an analysis of the impact of a change in the flight schedule of one or more airports interacting in a given area with a simulation able to deal with the stochastic components of the system. The framework, depicted in Figure 1, is composed by a simulator which, given the distribution of the total supply of each airport and how it is split among the existing flights of the airport, generates a series of scenarios. Each scenario is then used by a Logit model to calibrate the flow matrix (step 1), to simulate a given change in this matrix and to predict the new passenger flows. The output of each scenario is then used by the simulator in order to combine it with the other ones (step 2) and perform a statistical analysis on the aggregate results (step 3). In order to make a more accurate definition of the travel times and costs matrices, a georeference module is used. The georeference module is implemented by means of Google Earth APIs and it is also used to graphically represents the results of the DSS itself. Finally, a post-optimization software module is devoted to choose the best features of the new flight (e.g. the kind of aircraft, the number of flight). This module, given the estimated passenger flows, type of flight (domestic, European, etc.), airline, and the constraints of the single airport, gives a list of possible aircraft schedules.

The framework has been implemented in C++ and Math Kernel Library (MKL) to maximize the performances (Intel Corporation, 2010). The simulation phase has been implemented using Omnet++ 4.1 libraries (OMNeT Consortium, 2009).

In the following we focus our discussion on the Logit model in order to give an highlight of the optimization core of the framework.

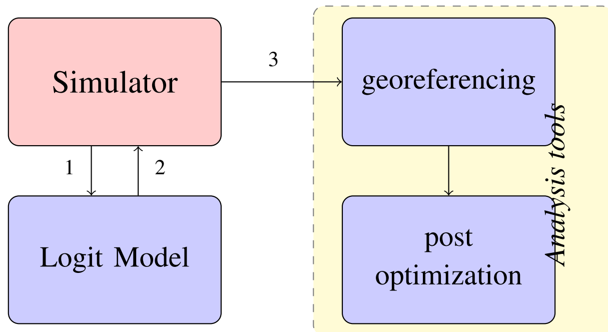

Figure 1: Block diagram of the framework.

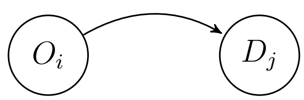

Figure 2: A representational of a single-level transportation networks.

3.1 Logit models

In this section we present the Logit models for the forecasting of the flows in an existing airport network used in AirCAST. The framework supports two variants of Logit models. The first one, depicted in figure 2, is a single-level model where passengers move from their origin to a destination representing the airports. We identify this model as one-level Logit that allows to evaluate the impact of a new route on competitor airports. The second is a two-level model and can represents intermodal or transshipment transportation networks. The structure of the modeled system is showed in figure 3, where the airports are usually the transshipment nodes H_k. In the following, we refer to this model as two-level Logit, which measures the economic impact of a new route on the destination areas.

Throughout this section x, $\boldsymbol{x}$ and $\mathbf{X}$ denote a generic scalar, vector (lowercase and boldface), and matrix (uppercase and boldface), respectively. Superscript $\widehat{}$ and $\widetilde{}$ will stand for the observed and estimated values, i.e. the values given to the Logit as input by simulator and the flows obtained after a parameter calibration, respectively.

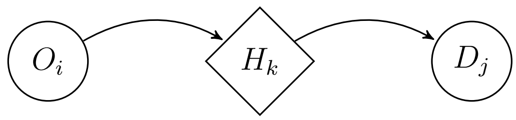

Figure 3: A representational of a two-level transportation networks.

3.1.1 Single-level logit model

Given a set of n origin airports, a set of m destination airports and $n \times m$ flights connecting them, we define

- identifier of origin airport $i \in \{1, \dots, n\}$;
- identifier of destination airport $j \in \{1, \dots, m\}$;
- observed flows matrix $\widehat{\mathbf{T}} \in \mathbb{R}^{n \times m}$, i.e. elements $\widehat{\mathbf{T}}_{i,j}$ give the number of passengers depart between i and j.
- generalized travel cost matrix $\widehat{\mathbf{C}} \in \mathbb{R}^{n \times m}$, i.e. elements $\widehat{\mathbf{C}}_{i,j}$ give the travel cost of the flight arriving in j and departing from the airport i.
- flight frequency matrix $\widehat{\mathbf{V}} \in \mathbb{R}^{n \times m}$, i.e. elements $\widehat{\mathbf{V}}_{i,j}$ give the number of flight from i to j in a fixed time period (usually, the weekly schedule).

We also define the total supply vector $\boldsymbol{o} \in \mathbb{R}^n$ in passenger of origin airports (1) and the total demand vector $\boldsymbol{d} \in \mathbb{R}^m$ of flights (2).

$$\boldsymbol{o} = \sum_j \widehat{T}_{i,j} \quad \forall i \tag{1}$$

$$\boldsymbol{d} = \sum_i \widehat{T}_{i,j} \quad \forall j \tag{2}$$

Our aim is to define a proper model for the estimated flows matrix $\widetilde{\mathbf{T}}$ considering both the operational characteristics of the flights connecting i and j, as well as the peculiar features of the destination airports. This model must be able to reproduce the matrix of the observed flows $\widehat{\mathbf{T}}$. To do that we develop a multinomial Logit model, which generates the estimated flows matrix, as well as the main parameters characterizing the system.

The Logit model is represented in (3) where $\boldsymbol{w} \in \mathbb{R}^m$ is an attraction factor of the flight destination j, β is a distance decay parameter and γ is the flight frequency decay parameter.

$$\widetilde{T}'_{ij} = o_i \frac{w_j \cdot e^{-\beta \widehat{C}_{ij}} \cdot e^{\gamma \widehat{V}_{ij}}}{\sum_j w_j \cdot e^{-\beta \widehat{C}_{ij}} \cdot e^{\gamma \widehat{V}_{ij}}} \tag{3}$$

In order to predict a change in the system due to a new flight or a schedule change, first we have to find the values of $\boldsymbol{w}$, β and γ characterizing the system and such that they reproduce the observed flows $\widehat{\mathbf{T}}$. This is done in the following calibration phase The procedure works al follows:

- Initialization. Set $\gamma_0 = \frac{2}{\overline{\nu}}$, $\beta_0 = \frac{2}{\overline{c}}$
- While the values of γ and β, and $\boldsymbol{w}$ changes over a given threshold or a maximum number of iterations is not reached
  - Given $\gamma_{\tau-1}$ and $\beta_{\tau-1}$, find the values of $\boldsymbol{w_\tau}$ which are the roots of the system
$$\boldsymbol{d} - \sum_i \widetilde{T}'_{i,j} = 0 \quad \forall j \tag{4}$$
  - Given $\boldsymbol{w_\tau}$ and $\beta_{\tau-1}$, find the new value of γ_τ by considering which is the root of the system
$$\sum_{i,j} (\widehat{\mathbf{V}} - \overline{\nu}) \widetilde{\mathbf{T}'} = 0 \tag{5}$$
  - Given $\boldsymbol{w_\tau}$ and γ_τ, find the new value of β_τ which is the root of the system
$$\sum_{i,j} (\widehat{\mathbf{C}} - \overline{c}) \widetilde{\mathbf{T}'} = 0 \tag{6}$$
- Find a correlation between $\boldsymbol{w}$ and the economical and structural features of the corresponding airports, indicated respectively $\widehat{\boldsymbol{\rho}} \in \mathbb{R}^m$ and $\widehat{\boldsymbol{\sigma}} \in \mathbb{R}^m$. The economical and structural features we consider are the total number of flights departing from an airport, the service time of the passengers, obtained as the sum of the time spent by a passenger in the airport before being his boarding and the time needed to access the airport by ground services as taxi, private car and train. This is done by a logarithmic transformation of the attraction factors estimated through linear regression. The correlation between $\boldsymbol{w}$ and two regression coefficients $\boldsymbol{\alpha}$ and δ is shown in (7).

$$\ln(\boldsymbol{w}) = \boldsymbol{\alpha} [\begin{matrix} \widehat{\boldsymbol{\rho}} \\ \widehat{\boldsymbol{\sigma}} \end{matrix}] + \delta \tag{7}$$

Equations (4) ensure that the estimate flows generates by the origin airport are equal to the airport demand, while (5) and (6) force the sum of the estimated flows weighted by $\widehat{\mathbf{V}}$ and $\widehat{\mathbf{C}}$ to be equal to the average number of flight and cost, respectively.

The calibration of $\boldsymbol{w}$, β, and γ is implemented by means of a fixed point algorithm, while the values of $\boldsymbol{\alpha}$ and δ are obtained by a linear regression. Notice that the procedure of system parameter estimation usually stops when the values of the parameters themselves at iteration τ do not differ from the values of iteration $\tau-1$ more than a given threshold, set to 10^{-3}. A second stopping criterion on the maximum number of iterations is given in order to prevent numerical issues.

By substituting equation (7) in (3), the new expression of the Logit model is

$$\widetilde{T}'_{ij} = o_i \frac{e^{\alpha_1\widehat{\rho}_j+\alpha_2\widehat{\sigma}_j+\delta} \cdot e^{-\beta\widehat{C}_{ij}} \cdot e^{\gamma\widehat{V}_{ij}}}{\sum_j e^{\alpha_1\widehat{\rho}_j+\alpha_2\widehat{\sigma}_j+\delta} \cdot e^{-\beta\widehat{C}_{ij}} e^{\gamma\widehat{V}_{ij}}}. \tag{8}$$

Even if the parameters have been accurately calibrated, they cannot take into account all the economical and structural features of the system. Thus, these factors are considered by a perturbation matrix $\boldsymbol{\Theta} \in \mathbb{R}^{n\times m}$. This matrix is defined by the ratio of observed flow in passenger ($\widehat{\mathbf{T}}$) to computed flow with Logit model ($\widetilde{\mathbf{T}}$).

$$\Theta_{ij} = \frac{\widehat{T}_{ij}}{\widetilde{T}'_{ij}} \quad \forall i,j \tag{9}$$

Each Θ_{ij} measures in percentage the impact of these unknown factors on the flow (i,j). Thus, the full expression of the estimated flows becomes

$$\widetilde{T}_{ij} = \Theta_{ij} \cdot o_i \frac{e^{\alpha_1\widehat{\rho}_j+\alpha_2\widehat{\sigma}_j+\delta} \cdot e^{-\beta\widehat{C}_{ij}} \cdot e^{\gamma\widehat{V}_{ij}}}{\sum_j e^{\alpha_1\widehat{\rho}_j+\alpha_2\widehat{\sigma}_j+\delta} \cdot e^{-\beta\widehat{C}_{ij}} e^{\gamma\widehat{V}_{ij}}}. \tag{10}$$

3.1.2 Two-level Logit model

Given a set of n origin, a set of m intermediate points and a set of r destination, we define

- identifier of origin $i \in \{1,\ldots,n\}$;
- identifier of intermediate points $j \in \{1,\ldots,m\}$;
- identifier of destination $k \in \{1,\ldots,l\}$;
- observed flows matrix $\widehat{\mathbf{T}} \in \mathbb{R}^{n\times m\times l}$, i.e. elements $\widehat{\mathbf{T}}^k_{ij}$ give the number of passengers depart between i and k using the intermediate point j.
- generalized flight cost matrix $\widehat{\mathbf{C_f}} \in \mathbb{R}^{n\times m}$, i.e. elements $\widehat{\mathbf{C_f}}_{ij}$ give the travel cost of the flight arriving in j and departing from the airport i.
- generalized travel cost matrix $\widehat{\mathbf{C_t}} \in \mathbb{R}^{m\times l}$, i.e. elements $\widehat{\mathbf{C_t}}^k_j$ give a possible travel cost between the intermediate point j and the destination k and an eventual subsistence cost in the destination k;

We also define the destination-dependent supply vector $\boldsymbol{o}^k \in \mathbb{R}^n$ of the origins (11), the total number of passengers at the intermediate points $\boldsymbol{d} \in \mathbb{R}^m$ (12) and the total demand of the destinations $\boldsymbol{r} \in \mathbb{R}^l$ (13) as follows:

$$\boldsymbol{o}^k = \sum_j \widehat{T}_{ij}^k \quad \forall i, k \tag{11}$$

$$\boldsymbol{d} = \sum_k \sum_i \widehat{T}_{ij}^k \quad \forall j \tag{12}$$

$$\boldsymbol{r} = \sum_i \sum_j \widehat{T}_{ij}^k \quad \forall j, k \tag{13}$$

As for the one-level model, our aim is to define a proper model for the estimated flows matrix $\widetilde{\mathbf{T}}$ considering both the avionic characteristics, as well as the peculiar features of the destination. This model must be able to reproduce the matrix of the observed flows $\widehat{\mathbf{T}}$.

The analytical expression for the flows is given by

$$\widetilde{T'}_{i,j}^{k} = o_i^k \cdot \frac{w_j \cdot \psi^k \cdot e^{-\beta(\widehat{C_f}_{ij} + \widehat{C_t}_j^k)}}{\sum_k \sum_j [w_j \cdot \psi^k \cdot e^{-\beta(\widehat{C_f}_{ij} + \widehat{C_t}_j^k)}]}. \tag{14}$$

where $\boldsymbol{w} \in \mathbb{R}^m$ is an attraction factor of the intermediate points, $\boldsymbol{\psi} \in \mathbb{R}^l$ is an attraction factor of the destinations and β is a distance decay parameter.

In order to predict a change in the system due to a new flight or a schedule change, the system parameters $\boldsymbol{w}$, $\boldsymbol{\psi}$ and β must be calibrated and such that they reproduce the observed flows $\widehat{\mathbf{T}}$. This is due by the following calibration phase. The procedure works as follows:

- Initialization. Set $\beta_0 = \frac{2}{\bar{c}}$ where $\bar{c} = \frac{\sum_{i,j,k} \widehat{T}_{i,j}^k (\widehat{C_f}_{i,j} + \widehat{C_t}_j^k)}{\sum_{i,j,k} \widehat{T}_{i,j}^k}$ and $\boldsymbol{\psi}_0 = \underline{\mathbf{1}}$
- While the values of β, $\boldsymbol{w}$ and $\boldsymbol{\psi}$ changes over a given threshold or a maximum number of iterations is not reached
  - Given $\beta_{\tau-1}$ and $\boldsymbol{\psi}_{\tau-1}$, find the values of $\boldsymbol{w_\tau}$ which are the roots of the system
  $$\boldsymbol{d}_j - \sum_k \sum_i \widetilde{T}'^k_{i,j} = 0 \quad \forall j \tag{15}$$
  - Given $\beta_{\tau-1}$ and $\boldsymbol{w_\tau}$, find the values of $\boldsymbol{\psi_\tau}$ which are the roots of the system
  $$\boldsymbol{r}^k - \sum_{i,j} \widetilde{T}'^k_{i,j} = 0 \quad \forall k \tag{16}$$

– Given $\boldsymbol{w_\tau}$ and $\boldsymbol{\psi_\tau}$, find the values of β_τ which are the roots of the system

$$\sum_{i,j}(\widehat{\mathbf{C}} - \bar{c})\widetilde{\mathbf{T}} = 0 \tag{17}$$

- Find a correlation between $\boldsymbol{w}$ and the economical and structural features of the corresponding intermediate points, indicated $\widehat{\boldsymbol{\Pi}}$. Every row of the matrix $\widehat{\boldsymbol{\Pi}}$ represents a different operative lever. This is done by a logarithmic transformation of the attraction factors estimated through linear regression. The correlation between $\boldsymbol{w}$ and two regression coefficients $\boldsymbol{\alpha_w}$ and δ_w is shown in (18).

$$\ln(\boldsymbol{w}) = \boldsymbol{\alpha_w}\widehat{\boldsymbol{\Pi}} + \delta_w \tag{18}$$

- Find a correlation between $\boldsymbol{\psi}$ and the economical and structural features of the destination, indicated in the matrix $\widehat{\boldsymbol{\Omega}}$. The correlation between $\boldsymbol{\psi}$ and two regression coefficients $\boldsymbol{\alpha_\psi}$ and δ_ψ is shown in (19).

$$\ln(\boldsymbol{\psi}) = \boldsymbol{\alpha_\psi}\widehat{\boldsymbol{\Omega}} + \delta_\psi \tag{19}$$

Meaning of equations (15), (16), and (17) is analogous to the single-level Logit model case.

The calibration of $\boldsymbol{w}$, $\boldsymbol{\psi}$ and β is implemented by means of a fixed point algorithm, while the values of $\boldsymbol{\alpha_w}$, $\boldsymbol{\alpha_\psi}$, δ_w and δ_ψ are obtained by a linear regression. The procedure of system parameter estimation uses the same stop criteria that is defined in the one-level Logit model calibration.

by substituting equations (18) and (19) in (14), the new expression of the Logit model is

$$\widetilde{T'}^{k}_{i,j} = \cdot o_i^k \cdot \frac{e^{\alpha_w \widehat{\Pi}_j + \delta_w} \cdot e^{\alpha_\psi \widehat{\Omega}_k + \delta_\psi} \cdot e^{-\beta(\widehat{C_f}_{ij} + \widehat{C_t}^k_j)}}{\sum_k \sum_j [e^{\alpha_w \widehat{\Pi}_j + \delta_w} \cdot e^{\alpha_\psi \widehat{\Omega}_k + \delta_\psi} \cdot e^{-\beta(\widehat{C_f}_{ij} + \widehat{C_t}^k_j)}]}. \tag{20}$$

Again, even accurately calibrated parameters cannot take into account all the economical and structural features of the system. Thus, these factors are considered by a perturbation matrix $\boldsymbol{\Theta} \in \mathbb{R}^{n \times m \times l}$. This matrix is defined by the ratio of observed flow in passenger ($\widehat{\mathbf{T}}$) to computed flow with Logit model ($\widetilde{\mathbf{T}}'$).

$$\boldsymbol{\Theta}^k_{ij} = \frac{\widehat{\mathbf{T}}^k_{ij}}{\widetilde{\mathbf{T}'}^k_{ij}} \quad \forall i, j, k \tag{21}$$

Each $\mathbf{\Theta}^k_{ij}$ measures in percentage the impascr of these unknown factor on the flow (i, j, k) Thus, the full expression of the two-level logit model, considering the perturbation matrix, is

$$\widetilde{T}^k_{i,j} = \Theta^k_{ij} \cdot o^k_i \cdot \frac{e^{\alpha_w \widehat{\Pi}_j + \delta_w} \cdot e^{\alpha_\psi \widehat{\Omega}_k + \delta_\psi} \cdot e^{-\beta(\widehat{C_f}_{ij} + \widehat{C_t}^k_j)}}{\sum_k \sum_j \left[e^{\alpha_w \widehat{\Pi}_j + \delta_w} \cdot e^{\alpha_\psi \widehat{\Omega}_k + \delta_\psi} \cdot e^{-\beta(\widehat{C_f}_{ij} + \widehat{C_t}^k_j)}\right]}. \tag{22}$$

3.2 Simulator

Given the Logit model, we can compute the new passenger flows by introducing the changes (e.g. the opening of a new flight or a flight cost change). The Logit models are able to deal with the uncertainties due to passengers choices, while they only partially consider the uncertainty due to demand and supply. To handle this, a modular simulator has been developed performing a scenario-based simulation integrated with the optimization block using the selected Logit model. Moreover, a set of data analysis and post-optimization tools are provided. The scenario-based simulation reduces the probability of error on the results and considers the changes in the flow of passengers over time. The scenarios are created by random modifications, with chosen probability distribution, of observed flows $\widehat{\mathbf{T}}$. The number of scenarios is defined *ad hoc* by the Relative Standard Deviation (RSD) of data set and must ensure that the solution is stable and the statistically independent of the simulation. A typical value of the error on the results of the simulation is 2%.

Once model has been calibrated on the scenario by the optimization block, the simulation process needs some input parameters that describe the changes in the system in terms of flight schedules and flight costs. In particular, the origin and the destination of new flight, the cost, the flight frequency and the number of flights of the selected flight. The changes of the flows are calculated as the difference between the flows $\widetilde{\mathbf{T}}$ obtained after introducing the new flights schedules and observed flows $\widehat{\mathbf{T}}$. This gives the new catchment area of the airports in terms of passengers, as well as a forecasts of the flows on each flight. The analysis block stores the results of the variation for each scenario and computes some statistical analysis on the new flows distributions. Simulating the impact of a set of new flight, the results are analyzed and are combined to give some statistics about the decisions. Finally, a post optimization process checks the solution that maximizes the effect on the airport of origin and chooses the parameters of the selected flight, i.e. flight frequency, airplane size.

Notice that the model can evaluate more than one new opening at a time and it is interesting to observe that it also allows to simulate reaction policies from the existing airports by assigning different values to their economical and structural features (e.g., an existing airport could choose to reduce its prices in order to face the competition of the new flight).

4 Computational tests: two Italian airports case studies

In order to validate the framework, we simulate the consequences of opening new flights in Bolzano airport (in the following ABD) and in Cagliari airport (in the following CAG). We considered the case of opening new flights between a panel of given destinations, selected from the database of International Air Transport Association (IATA).

The catchment areas of the airports generates a stochastic supply, which is considered to be uniformly distributed, while the other data (costs, flight frequency, access times) have been taken from public documents of the airports themselves and the databases of Eurostat and IATA. Other important statistics are provided by (ENAC, 2008), (ENAC, 2009), (ENAC, 2010) and (ISTAT, 2009). The forecasts generated by the framework have been validated by BDS s.r.l., a consulting company specialized in the air transportation market, and specialized staff by Bolzano and Cagliari airports.

4.1 Bolzano - Dolomiti

Bolzano Dolomiti Airport was born in 1992 and the work of modernization of the structure was completed in 1999. The offer of flights provided by ABD Airport is very limited and the only possible flight is between Bolzano and Rome with daily frequency of four times per day (two in the morning and two in the afternoon). The connections of the ABD Airport are showed in figure 4.

We want to predict the opening of a new route to manage the flow of passengers from the airport to a chosen destination. This type of problem is modeled by the one-level Logit. The simulations performed on ABD Airport aim to establish the route, the type of aircraft, the flight frequency and type of airline (business or low cost) that allows to attract the highest number of passengers.

Figure 4: Current flights offer provided by ABD Airport.

Parameter setting

In this case study we used the single-level Logit model. For the economical and structural features used to calibrate $\boldsymbol{\alpha}$ and δ, we considered are the total number of flights departing from an airport, the service time of the passengers, obtained as the sum of the time spent by a passenger in the airport before being his boarding and the time needed to access the airport by ground services as taxi, private car and train. This is done by a logarithmic transformation of the attraction factors estimated through linear regression.

The catchment area is focused on the residents of Bolzano area moving in neighboring countries for business and tourists who come from all over Europe for the summer or winter holidays. Analyzing the socioeconomic conditions of Bolzano and some statistic surveys on data supplied by the provincial statistic istitute (ASTAP) and on samples of users of ABD Airport, the cluster of destinations and the set of competitors have been defined. The identified macro-areas are Germany, Austria and Switzerland and the respective centroid are Frankfurt, Vienna, Zurich. Similarly, we defined the cluster of sources such as airports easily reachable from Bolzano. In particular, competitors are Venice, Verona, Treviso, Innsbruck, Salzburg and Monaco.

For each route, we define the possible price ranges and the flight frequency. The cost is considered excluding airport taxes and typical ranges are currently

Destination	Flights per day	$\overline{T}_{200}$	$\overline{T}_{300}$	$\overline{T}_{500}$
Frankfurt	2	5968	5140	4426
Frankfurt	4	32504	28078	24243
Wien	2	3833	3302	2844
Wien	4	19154	16553	14297
Zurich	2	2205	1890	1636
Zurich	4	12272	10605	9160

Table 1: Average flows in passengers ($\overline{T}_x$) after the opening of the new flights, where x is the price of the route.

- Low : cost lower than 200 €.
- Medium : cost ranges between 200 €and 300 €.
- High : cost ranges between 300 €and 500 €.

According to the usual schedules of ABD Airport, simulation considers a low frequency (two aircraft per day) and a high frequency (four aircraft per day). After a calibration phase, we set the number of scenarios to 30.

Simulation phase

The simulation results are summarized in tables 1 and 2 (first two rows) and in Figure 5. In particular, we show the outgoing flows from ABD Airport grouped by price ranges and by flight frequency in table 1 and the simulated flows of competitors due to the opening of the flight ABD Airport - Frankfurt in table 2.

The Bolzano-Frankfurt route provides the largest flows area for both frequency values and for different ticket price range. The validity of the solution is demonstrated by data on tourism of Bolzano, which certify the presence of a large German component on the territory. The optimal setting is given by an high frequency flight schedule with a low-cost airline.

Verona airport is the competitor which has contributed most to the flow of new offer. The following section examines the involvement of Verona to address the reduction in passengers.

Figure 5: Results of the three simulated flights with four daily flights. A bar chart shows the intercepted flow by each route. The bands of low, medium and high cost are indicated by green, yellow and orange bars, respectively (example of georeferencing generated by the framework).

Reaction phase

The simulation of a reaction of an airport is a long-term analysis and it assumes that the new route has become a reality. One possible operation is to reduce the cost of the ticket that is more affected by the new system or the transition to a low-cost airline.

We have created two scenarios. The first reduces the price of the route Verona-Frankfurt to a Medium range. The second reduces further the cost to a Low range of costs and requires some capital investment for the research and the opening of a low-cost airline and an average aircraft load factor equal to 72%. Both simulations allow to attract part of the catchment area. In particular, the introduction of a low-cost airline offers a number of passengers greater than the initial one. Flows of the entire system are shown in the last two rows of Table 2 and in Figure 6.

The price reduction affects all of the competitor airports. In more details, while the losses are marginal when Verona changes its price to a medium range, it becomes more relevant when a low-cost flight is introduced, especially for Munich ($\Delta_{\mathbf{T}_L} = -12601$), Salzburg ($\Delta_{\mathbf{T}_L} = -3836$) e Venice ($\Delta_{\mathbf{T}_L} = -2805$). Their losses are negligible when compared to the total flow of each airport and will hardly lead to a subsequent reaction step. Similarly, the transition to a low-cost does not affect the number of passengers using the route Bolzano - Frankfurt, which can coexist with other routes of the analyzed system.

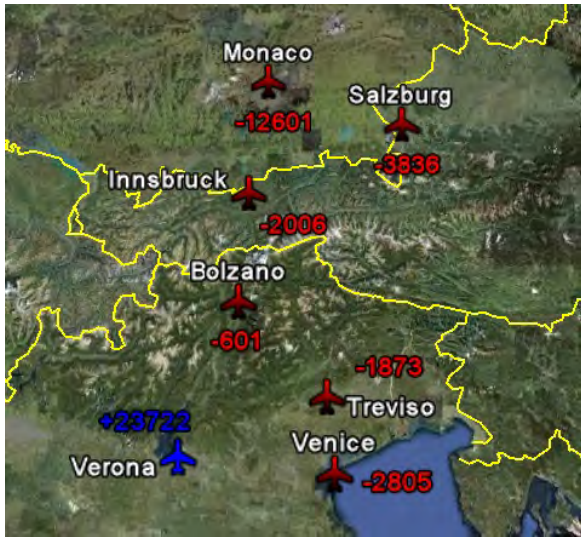

Figure 6: Results of the simulator due to moving to a low cost airline from Verona. The blue and red numbers indicate which airports have a positive or negative variation of flow.

Additional transport costs

So far, the performed simulations did not consider the costs of transportation to the origin airport. Analyzing the situation of Bolzano the real cost that a user has to support in order to reach a competitor airport must be considered.

The total cost of a route is defined in the equation 23, where C_{air} is the cost of air ticket, C_{train} is the cost of the train ticket that connects Bolzano with competitor airports, K and t_{car} represent constants that quantify the time spent to move in euro and the travel time by car from Bolzano, respectively.

$$C_{tot} = C_{air} + C_{train} + K \cdot t_{car} \qquad \forall j \tag{23}$$

Simulating the system with the same price ranges and the same frequencies of the flight, we achieved the results in table 3. Even in this case, the route to Frankfurt provides a greater catchment area if it is associated with a low-cost airline and a high frequency of flights. The increasing of simulated flow is due to the introduction of additional costs; the decision of the users is also characterized by a spatial factor (i.e. the distance from the origin).

80% of attracted passengers by the new route comes from Verona, which will establish the reaction policies (i.e. reduction of the ticket price and the transition

	Bolzano	Verona	Venice	Treviso	Innsbruck	Salzburg	Munich
$\mathbf{T}$	0	121350	150852	109231	105199	164416	1243272
$\Delta_{\mathbf{T}_O}$	32504	-20618	-1288	-653	-900	-3412	-5633
$\overline{\mathbf{T}}_O$	32504	100732	149564	108578	104299	161004	1237639
$\Delta_{\mathbf{T}_M}$	-169	7834	-822	-431	-624	-1712	-4076
$\overline{\mathbf{T}}_M$	32335	108566	148742	108147	103675	159292	1233563
$\Delta_{\mathbf{T}_L}$	-601	23722	-2805	-1873	-2006	-3836	-12601
$\overline{\mathbf{T}}_L$	31903	124454	146759	106705	102293	157166	1225038

Table 2: Summary of main results. The table reports the observed flow ($\mathbf{T}$), the flow after the opening of the flight Bolzano-Frankfurt ($\overline{\mathbf{T}}_O$) and the reactions of Verona with the transition to a medium and low-cost flight ($\overline{\mathbf{T}}_M$ and $\overline{\mathbf{T}}_L$, respectively) and their variations ($\Delta_{\mathbf{T}_M}$ and $\Delta_{\mathbf{T}_L}$).

Table 3: Average flows in passengers ($\overline{T}_x$), where x is the price of the route. In this case the simulator considers the real costs of flight.

Destination	Frequency	$\overline{T}_L$	$\overline{T}_M$	$\overline{T}_H$
Frankfurt	2	6450	5556	4785
Frankfurt	4	35390	32109	26411
Wien	2	4085	3698	3031
Wien	4	20578	18576	15369
Zurich	2	2315	2096	1717
Zurich	4	12993	11790	9703

	Bolzano	Verona	Venice	Treviso	Innsbruck	Salzburg	Munich
$\mathbf{T}$	0	121350	150852	109231	105199	164416	1243272
$\Delta_{\mathbf{T}_O}$	35390	-28495	-534	-68	-377	-3406	-2510
$\overline{\mathbf{T}}_O$	35390	92855	150318	109163	104822	161010	1240762
$\Delta_{\mathbf{T}_M}$	103	-3511	596	632	474	-460	2166
$\overline{\mathbf{T}}_M$	35493	89344	150914	109795	105296	160550	1242928
$\Delta_{\mathbf{T}_L}$	-288	9803	-1065	-577	-686	-2229	-4958
$\overline{\mathbf{T}}_L$	35102	102658	149253	108586	104136	158781	1235804

Table 4: Summary of simulation that considers the additional costs. The table reports the observed flow ($\mathbf{T}$), the flow after the opening of the flight Bolzano-Frankfurt ($\overline{\mathbf{T}}_O$) and the reactions of Verona corresponding to the lowering the price ($\overline{\mathbf{T}}_M$) and to the transition to a low-cost flight ($\overline{\mathbf{T}}_L$) and their variations ($\Delta_{\mathbf{T}_O}$, $\Delta_{\mathbf{T}_M}$ and $\Delta_{\mathbf{T}_L}$).

to a low-cost airline).

In Table 4 we present the results of the simulation of a reduction of ticket price by Verona in order to be more competitive on the flight to Frankfurt. The simulation results show that simply reducing the cost from High to Medium is not enough and implies a further loss of passengers of $\Delta_{\mathbf{T}_M} = -3511$. The introduction of a low-cost flight ensures an increase in the catchment area, however, the final flow is reduced by about 15% compared with the observed values.

The route Bolzano - Frankfurt is not influenced by the reaction policies of Verona. The variation of the flow is less than 1%, given that the survival of the route is guaranteed.

4.2 Cagliari

In Sardinia there are three airports: Alghero in the province of Sassari in the north-west of the island, Olbia Costa Smeralda in the province of Olbia-Tempio situated in the north-east and Cagliari in the south. Cagliari is the island most important airport in terms of traffic and size. In fact, it operates about 50% of the air traffic and can accommodate about 4 million passengers. In 2009, as in the recent past, the sustained growth trend in air traffic was matched by high quality standards: thanks to consolidation of national and international direct links and the opening of 21 new routes, the CAG Airport has for the first time reached the 3 million passenger mark, gaining more than 13% on the previous year.

However, although Cagliari attracts more passengers than the other two airports in Sardinia, the distribution of flights is quite different. On some routes, offering flights is much lower or even absent. In particular, Cagliari does not offer direct flights with Eastern Europe (see figure 7(a)), e.g. Russia, Estonia, Lithuania, Romania, Bulgaria. Almost all the Eastern European tourists come from Russia. Conversely, there is a strong component in the macro-area of Alghero from Northern Europe and especially from Finland, Sweden, Denmark, Ireland and Norway. Olbia airport offers, instead, connections to Central and Northern Europe and a high number of passengers come from the Netherlands. The only routes that are shared by all airports are from Austria, Belgium, France, Germany, Great Britain and Spain.

Aim of this case study is to predict the effect of opening of one or more new routes on the flow of passengers from chosen origins to CAG Airport and to measure the economic impact on the close area, showed in figure 7(b). The simulations performed on CAG Airport aim to establish the route, the type of airline (business or low cost) and the season (high or low) that allow to attract the highest number of tourists.

Parameter setting

The Logit model used in this application is the Two-level one. The catchment area is focused on the tourists arriving in neighboring area of Cagliari from all over Europe for the summer holidays. Analyzing the socio-economic conditions and airport data emerged from the analysis carried by ISTAT (2009), the sources cluster has been identified composed by Northern Europe (Sweden, Norway and Finland), Central Europe, Netherlands and Russia. Similarly, we defined the cluster of arrival airports and macro-areas for the tourist holidays as Cagliari, Olbia and Rimini. In particular Rimini has been chosen being the reference airport for a large community of Russian tourists in Emilia Romagna. The flow of tourists to the area of Alghero is not comparable with others and was not included in the simulation. The only destination k is Italy. We introduced this macro-destination in order to let the model to move flows from one airport to another.

Figure 8 show all actors involved in the simulation.

The operative levers used in the simulation are one for the airport operations and one related to the socio-economic situation of the touristic region around each airport. The operations lever identifies the airport depending on the presence or not of direct flights between the airport of origins. The economic lever is a level of customer satisfaction of the destination related to the ground transportation from the arrival airport, the services offered to tourists and the cost of subsistence obtained by averaging the prices of hotels (ISTAT, 2009).

As shown by Perfetti (2011) and by the summary flow in table 5, the low percentage of Russian tourists in the Cagliari leads to consider opening a direct route between Russia and Cagliari. The same conclusion was drawn, considering the attraction factor, direct connected with the number of tourists, of the Olbia's area carried on the other countries of origin. In particular, the following scenarios are interesting:

- CAG Airports open a direct flight to Russia in the high season.
- Measurement of the reaction of Olbia Airport, which opens a direct flight to Russia.
- CAG Airport opens a direct flight to Russia in the low season.

Table 5: Number of tourists in the destination group by origins.

	Cagliari	Olbia	Emilia
Russia	6,908	4,534	74,705
Northen Europe	7,209	17,082	16,775
Netherlands	13,039	97,277	19,916
Central Europe	174,583	254,971	182,650

Calibrating the number of scenarios, a stable solution is obtained by simulating 20 scenarios.

Simulation phase

The first simulation consists in opening a direct flight between Cagliari and Russia in the high season (July and August) which includes the reduction of the cost of the ticket. Currently, the connection with Russia requires at least one stop at the airport of Rome. The new simulated flow of tourists is showed in table 6.

The increase of Russian tourists in the Cagliari's area is estimated at about 90%. From an economic point of view, the analysis of ISTAT (2009), revenues on the territory from direct effects can be valued to about 12 million euros. Rimini airport, despite being the competitor that has contributed most to the flow of new avionics offer, can not respond to reductions of tourists as already offers a direct flight from Russia.

Table 6: Summary of simulation. The table reports the observed flow ($\mathbf{T}$), the flow after the opening of the direct flight Cagliari-Russia in high season ($\overline{\mathbf{T}}_D$) and its variation ($\Delta_{\mathbf{T}_D}$).

	Cagliari	Olbia	Emilia
$\mathbf{T}$	6908	4534	74705
$\Delta_{\mathbf{T}_D}$	6198	-355	-5843
$\overline{\mathbf{T}}_D$	13106	4179	68862

Assuming that the new route between Russia and Cagliari has become a reality, also Olbia could open a direct flight from Russia to address the cascading effects of the new offer of CAG Airport. The simulation results (table 7) show an increase of tourists in the Olbia area of 120% and a negligible variation in the close area of Cagliari. Consequently, the two open routes can coexist.

Table 7: Summary of simulation. The table reports the observed flow ($\mathbf{T}$), the flow after both airports in Sardinia open the direct flight to Russia in high season ($\overline{\mathbf{T}}_D$) and its variation ($\Delta_{\mathbf{T}_D}$).

	Cagliari	Olbia	Emilia
$\mathbf{T}$	6908	4534	74705
$\Delta_{\mathbf{T}_D}$	5241	5630	-10871
$\overline{\mathbf{T}}_D$	12149	10164	63833

The last simulation consists in opening a direct route between Russia and Cagliari in low season (September and October) which involves, in addition to the reduction of the flight ticket, a decrease of the cost of subsistence in the territory. In fact, in this period the hotels offer some discounted fares. Table 8 shows an increase of Russian tourists by 225% which,in an economic point of view, corresponds to a income of about 20 million euros.

Table 8: Summary of simulation. The table reports the observed flow ($\mathbf{T}$), the flow after the opening of the direct flight Cagliari-Russia in low season ($\overline{\mathbf{T}}_D$) and its variation ($\Delta_{\mathbf{T}_D}$).

	Cagliari	Olbia	Emilia
$\mathbf{T}$	6908	4534	74705
$\Delta_{\mathbf{T}_D}$	15542.96	-889.36	-14653.6
$\overline{\mathbf{T}}_D$	22450.96	3644.64	60051.4

5 Conclusions

In this paper a simulation-optimization framework for the optimization of flight connections in a monomodal and an intermodal transport system has been presented. The framework is able to consider both stochasticity due to the uncertainty of the data and to represent the choices due to the reaction of customers to a change in the airport system under study.

Two real tests on regional Italian airports, one on airport of Bolzano and one on airport of Cagliari, show that the framework is able to forecast the new flows and the economical impacts due to the opening or the changing of the flight connection, as well as to take into account the reaction of competitors due to this opening.

From a computational point of view, the forecast can be obtained with a negligible computational effort (less than a minute for a full run of the simulation with 5 competitors over a total of 15 flight destinations and 50 scenarios).

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References

Ashford, N. and Bencheman, N. (1987). Passengers' choice of airport: an application of the multinomial logit model, *Transportation Research Record* **1147**: 1–5.

Baik, H., Trani, A. A., Hinze, N., Swingle, H., Ashiabor, S. and Seshadri, A. (2008). Forecasting model for air taxi, commercial airline, and automobile demand in the united states, *Transportation Research Record: Journal of the Transportation Research Board* **2052 / 2008**: 9–20.

Better, M., Glover, F., Kochenberger, G. and Wang, H. (2008). Simulation optimization: Applications in risk management, *Int. J. Inform. Tech. Decis. Making* **7**: 571–587.

Brooke, A. S., Caves, R. E. and Pitfield, D. E. (1994). Methodology for predicting european short-haul air transportat demand from regional airports: an application to east midlands international airport, *Journal of Air Transport Management* **1**: 37–46.

ENAC (2008). Traffic data of the italian airports, *Technical report*, Italian Civil Aviation Authority.

ENAC (2009). Traffic data of the italian airports, *Technical report*, Italian Civil Aviation Authority.

ENAC (2010). Traffic data of the italian airports, *Technical report*, Italian Civil Aviation Authority.

Hess, S. and Polak, J. (2004). On the use of discrete choice models for airport competition with applications to the san francisco bay area airports, *10th triennial World Conference on Transport Research, Budapest*.

Hess, S. and Polak, J. (2005a). Accounting for random taste heterogeneity in airport-choice modelling, *Transportation Research Record* **1915**: 36–43.

Hess, S. and Polak, J. (2005b). Mixed logit modeling of airport choice in multi-airport regions, *Journal of Air Transport Management* **11**: 59–68.

Hess, S. and Polak, J. (2006). Exploring the potential for cross-nesting structures in airport-choice analysis: a case study of the greater london area, *Transportation Research E* **42**: 63–81.

IATA (2008). World air transport statistics 53rd edition, *Technical report*, International Air Transport Association.

IATA (2010). World air transport statistics 55th edition, *Technical report*, International Air Transport Association.

Intel Corporation (2010). *Intel Math Kernel Library Reference Manual*.

ISTAT (2009). Arrivals and nights spent in accommodation by region, province and country of residence clients, *Technical report*, Italian National Institute of Statistics.

Koppelman, F. and Wen, C. (2000). The paired combinatorial logit model: properties, estimation and application, *Transportation Research B* **34**: 75–89.

Olafsson, S. and Kim, J. (2002). Simulation optimization, *in* E. Yucesan and C. H. Chen (eds), *Proceedings of the 2002 Winter Simulation Conference*, pp. 79–84.

OMNeT Consortium (2009). *OMNeT++ 4.0 User Manual*.

Pels, E., Nijkamp, P. and Rietveld, P. (2001). Airport and airline choice in a multi-airport region: an empirical analysis for the san francisco bay area, *Regional Studies* **35**: 1–9.

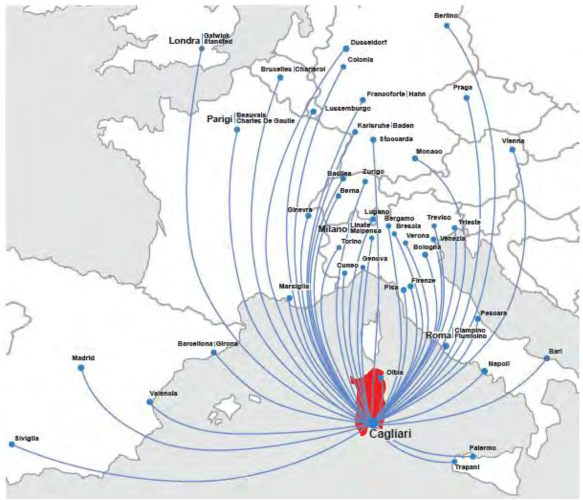
Pels, E., Nijkamp, P. and Rietveld, P. (2003). Access to and competition between airports: a case study for the san francisco bay area, *Transportation Research A* **37**: 71–83.

Perfetti, F. (2011). *Analysis of the economic impact of airport services in sardinia*, Master's thesis, Politecnico di Tornino.

Tadei, R., Ricciardi, N. and Perboli, G. (2009). The stochastic p-median problem with unknown cost probability distribution, *Operations Research Letters* **37**: 135–141.

Tadei, R., Ricciardi, N., Perboli, G. and Baldi, M. M. (2010). An efficient heuristic for the transshipment location problem under uncertainty with lower and upper capacity constraints, *CIRO*.

Thompson, A. and Caves, R. (1993). The projected market share for a new small airport in the north of england, *Regional Studies* **27**: 137–147.



(a) Current national and international flights offer provided by CAG Airport.

(b) Isochrones of CAG Airport. In dark green places take 1 hour to travel by car and in light green places take 2 hours.

Figure 7: Situation of the airport of Cagliari.

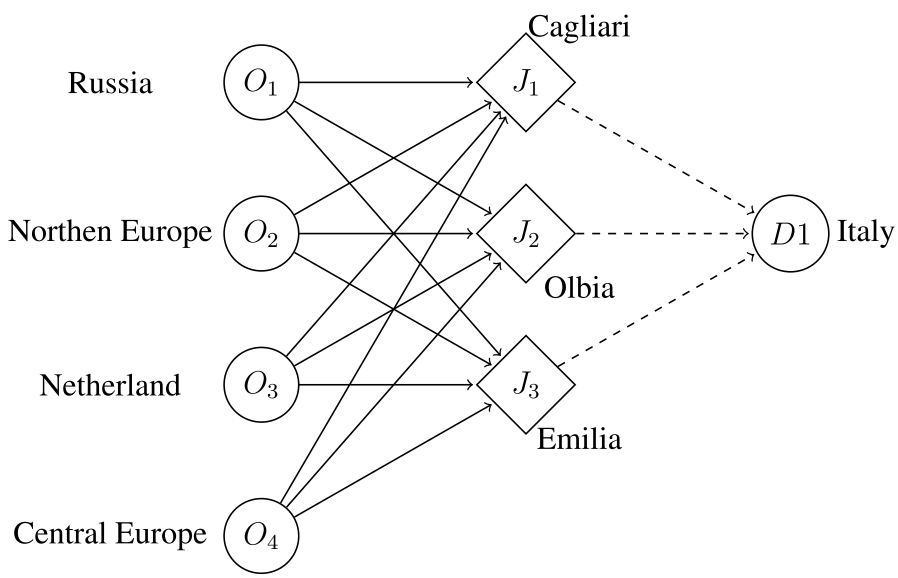


Figure 8: A rappresentantion of the catchment area in the case of Cagliari ariport.